A Big Data Analytics Method for Tourist Behaviour Analysis

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A big data analytics method for tourist behaviour analysis

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Highlights

- This paper introduces a big data analytics solution for destination management organization's decision support
- The design artifact is specified as a 'method' to analyse the social media data to support strategic decision-making in tourism
- Proposed solution method has the capability to provide insight of tourist's behavioural patterns at destinations.
- The capability of the solution method is demonstrated in a case study of inbound tourists to Melbourne, Australia.

Abstract

Big data generated across social media sites has created numerous opportunities for bringing more insights to decision-makers. Few studies on big data analytics, however, have demonstrated the support for strategic decision-making. Moreover, a formal method for analysing social media-generated big data for decision support is yet to be developed, particularly in the tourism sector. Using a design science research approach, this study aims to design and evaluate a 'big data analytics' method to support strategic decision-making in tourism destination management. Using geotagged photos uploaded by tourists to the photo-sharing social media site, Flickr, the applicability of the method in assisting destination management organisations to analyse and predict tourist behavioural patterns at specific destinations is shown, using Melbourne, Australia, as a representative case. Utility was confirmed using both another destination and directly with stakeholder audiences. The developed artefact demonstrates a method for analysing unstructured big data to enhance strategic decision making within a real problem domain. The proposed method is generic, and its applicability to other big data streams is discussed.

Keywords: tourism destination management; tourist behaviour; big data; predictive analytics; strategic decision support

1. Introduction

The voluntary sharing of personal information and uploaded contents on various online social networks has created several opportunities for the useful analysis. Multiple types of data are continuously growing within social media sites (such as Twitter, Facebook, Flickr, etc.) due to the huge number of users' voluntary posts and digital photo and video uploads. Infographic [28] suggests that YouTube users upload 72 h of new video files per minute, which is indicative of the very large amount of data that must be handled in any real-world analytics project. However, traditional data management approaches are capable neither of managing such a large and diversified amount of data nor of handling its effective growth and maintenance as the volume and velocity of relevant data increase [4; 27; 73].

Big data is characterised by its *Volume* (much bigger than traditional data sets), *Velocity* (the rapid speed with which it is produced and available), *Variety* (of formats in particular), *Variability* (over time and diversity of sources), and *Volatility* (inconsistent levels of production) [57]. 'Big data analytics' describes the activities involved in the specification, capture, storage, access and analysis of such datasets to make sense of its content and to exploit its value in decision-making [22]. Big data has attracted increasing attention by researchers and business decision-makers: examples in tourism include knowledge generation for strategic planning purposes in tourism destinations (TDs) [18], hospitality management [74], customer relation management [56] and destination marketing [47]. Although social media has been considered as a useful and reliable source of tourist information [68], the analysis of big data generated particularly through social media remains underexplored, particularly in TD management. In this study, we focus on supporting strategic decision-making in this sector, because, in general, big data analytics has not yet provided use cases for strategic decision support [57].

A TD can be described as a geographical area that offers tourists the opportunity of participating in a variety of attractions and activities and an area that is supported by all the hospitality and other services that the visitor might require. Fundamentally, a TD is a collection of physical locations in which tourists spends their time and visits for sightseeing (both constructed and natural sites), participating in activities (e.g. swimming, skiing and learning) and enjoyment (e.g. visits to bars, events, shops and restaurants). Destination management organisations (DMOs) are responsible, in general, for managing and promoting the TD, liaising with the local tourism industry and leading development strategies. Therefore, they must be alert to the needs of future marketplace and collaborations among the various stakeholders involved [19; 71].

In this context, the big data generated by individual tourists, in the form of content/materials for online sharing, may hold interesting and useful insights. This big data is available at various social media sites used for photo sharing (Flickr), video sharing (YouTube), immediate response sharing (Twitter), photo & comment sharing and discussion (Facebook). Such data are rarely collected by tourism authorities, despite the fact that it might offer important insight into tourists' behaviour and preferences relevant to TD management. Current technologies for analysing and converting such big data into meaningful decision support information are not widely available outside large corporations. In part, this is because that the massive volume and variety of the big data sets extend beyond the scope of the more common analytics tools [4].

A major challenge in TD management is how to track the behaviour of tourists. Destination managers need to know the details of specific locations visited by tourists, what attracts tourists at each location, personal reflections on tourists' experiences and future travel behavioural intentions. In general, most current approaches are unable to address these issues in a decision-centric, integrated and comprehensive manner. Most of the existing methods for analysing social media data are focused on finding answers to specific questions that are predefined in their studies (e.g. [10; 53]) and not on developing a general understanding of tourists' movement, interests and experiences (e.g. [41; 77]). Some location-based analytics methods are specialised for analysing spectral or GPS-tracked data to extract flows and patterns of tourist movement within particular regions [8]. Parameterisation of spatial and temporal dimensions is non-trivial, depending critically on GPS accuracy, threshold choices and often prior limited knowledge of the dataset: such approaches also suffer from size of cell that affects summary statistics in the case of spatially aggregated data, and likewise the temporal resolution of the observations [54]. Patterns identified by them neither indicate the semantics of visitor movements nor demographic variations; thus, it seems imperative that new analytic methods, considering information implicit in big data, are required for DMO's strategic decision-making.

The proposed study goes beyond previous studies in using design science research (DSR) methodology to develop and evaluate a new analytics method based on unstructured big data but with content meaningful in tourism-focussed terms. Our method integrates established and emerging computational techniques to allow various management-driven parameterisations, and in this paper, we specify the details of our proposed design artefact as a destination-management strategic planning and operational decision support tool.

A DSR methodology is adopted, where the seven design guiding principles of Hevner et al. [25] are used to design, evaluate and communicate the solution. As defined by March and Smith [46], our design artefact is specified as a "method"[1] designed to process and analyse social media big data, such as geotagged photos, together with their associated personal and meta-data, to support DMO's strategic decision-making within the context of TD management.

Our solution method combines four computational techniques such as text processing, geographical data clustering, visual content processing and time series modelling to more comprehensively address the DMO's decision support needs. This method has the capability to provide insight into tourists' behaviour, and to assist with the forecasting of future and seasonal demands for the purposes of tourism development, management and planning. Using geotagged data allows unstructured social media to be analysed and categorised numerically by using algorithms such as the density-based cluster algorithm proposed by Kisilevich et al. [34] to identify, for example, attractive places.

The remainder of the paper is structured as follows. Section 2 overviews the background literature relevant to the design of the solution artefact. Details of the research study methodology are discussed, and, in the subsequent section, we specify details of the design artefact, describing our contribution in the context of previous, relevant work. We then demonstrate the value of the artefact, according to utility, usability and accuracy criteria, within a representative case context. The discussion section highlights overall contributions of the study, followed by the conclusion section that includes the details of study limitations and identification of avenues for further research.

2. Literature overview

In this section, we first introduce the big data paradigm, with an emphasis on unstructured user-generated posts in social media within the context of their potential benefit to tourism decision-making. We then focus on the application of analytics solution in tourism, particularly for TD management, to highlight the importance of designing a new analytics method for DMO's strategic decision support.

2.1 Social media as big data source

[1] A method as a design research artefact specifies a way to perform goal-directed activities. It defines processes and provides guidance on how to solve problems. Methods can range from "formal, mathematical algorithms that explicitly define the search process to informal, textual descriptions of best practice approaches, or some combination" [25, p.79].

"Big Data" refers to the very large datasets that are increasingly available as digital activity increases. The data recorded through CCTV cameras, GPS and sensor networks, and the increased communication using digital texts, uploaded photos and blog posts mean that huge amounts of data are potentially available for analysis. Big data is classically characterised not just as voluminous, but also having variety (different types) and having velocity, in that it is often available in real- or near-real time. A formal definition has been proposed by De Mauro et al. [16, p. 131]: "Big Data is the Information asset characterised by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value." Variant definitions suggest veracity, volatility (variability) and so on to reflect particular aspects of datasets.

"Social Media" is defined as a "generic term for social interactions built on a multitude of digital media and technologies, which allow users to create and share content and to act collaboratively" [59, p. 3]. Social media provides voluminous, varied and velocitous data of potential value to decision makers and is a rich source for big data [31]. Social media data are generated by the popular use of social networking applications and websites, such as Facebook, Twitter, LinkedIn, Tumblr, TripAdvisor, YouTube and Flickr. Content includes user-produced blog posts about real-time activity, photos, short videos (typically but not necessarily), brief comments or opinions and professional or personal information. The widespread growth of social media sites allows voluntary public sharing of such information and has created a new and extensive global society of always-connected people enthusiastic about sharing, interacting and collaborating [13; 14].

Travel blogs, online travel reviews and online consumer reviews are all rich sources of big data. Studies, such as those of Marine-Roig and Clavé [47] and Xiang et al. [74], suggested that big data provides a huge amount of detail that contains deep-structure information on experiences, feelings, interests and opinions. In general, authors agree on the strategic value of big data in the field of tourism [35; 42; 47] in areas relevant to DMOs, such as the construction of destination image through the electronic word-of-mouth effect [26; 29].

2.2 Big data analytics and tourism

Big data, which can be viewed as a 'new era' of the data-driven paradigm, has opened up new possibilities for the improved decision support [57]. Although research is at an early stage (e.g.

predominantly for information systems design), these possibilities directly apply in data-intensive industries such as tourism, particularly for DMOs in the context of TD planning and operations. However, most existing support tools are not capable of coping with the sheer volume and rich data diversity that characterises the domain, as well as the data management required given expanding growth of datasets and user-produced content. In most cases, databases, rules, models and other traditionally relevant technologies and methods employed in decision support systems were not designed to work with social media data: instead, these work best with highly structured data [15; 67]. In contrast, 95% of big data is unstructured, necessitating the development of new analytic tools and techniques specific to the properties of big data sets [22]. Big data analytics leverages multiple datasets from a heterogeneous variety of associated media and metadata to drive decisions concerning the future, and predictive analytic techniques designed for smaller, structured data sets will have to be adapted, complemented or replaced. With regard to predictions, Conway and Klabjan [11] noted that the existing forecasting models (and relevant visualisations) can be improved by the "more granular record of the past" afforded by big data's more accurate inputs [p.135].

Various new analytics approaches and frameworks have been proposed under the umbrella of the social media and big data paradigm. We classified the analytics applications into two subgroups: (a) social media analytics in general and (b) social media analytics in tourism. Both the groups use data generated through social media, but the former refers to the analytics for general business applications, whereas the latter refers to analytics specifically relevant to tourism management. The following paragraphs discuss these groups in detail.

Outside of the tourism domain, many attempts have been made to develop effective analytics solutions. Musto et al. [50] employed a semantic analysis to map social media content (posted by a community of citizens) to social capital indicators (such as feelings of trust and safety) by using an opinion mining technique called *SentiWordNet*. Each social indicator is measured with a positive or negative synthetic aggregated score. He et al. [24] developed a "social media competitive analytics" tool called *VOZIQ*, for the calculation of sentiment benchmarks from tweets to enhance business performance. Another social business intelligence analytics application, employing online analytical processing techniques, has been developed, which combines corporate databases and user-produced big data to better inform the determination of business trends and customer mood within the business environment [20]. Organisation-specific social media big data has also been used to enhance managers' understanding of stakeholders' concerns to better inform managerial decisions relating to stakeholders and their connection with major events [30].

In tourism context, most analytics have centred on travel recommender systems (TRS), though earlier systems rarely used social media and were not designed for use by DMOs. Kurashima et al. [36] used the sequence of locations in tourists'-shared geotagged photos to identify and recommend travel routes that can be personalised according to interests and time available. Shi et al. [60] used geotagged photos sourced from Flickr to recommend landmarks, personalised to individual users, which reflect their specific tastes, not necessarily the most popular landmarks. Similarly, Khotimah et al. [32] proposed a TRS that extracted data from various social media in Indonesia to provide a user-related recommendation that can overcome the sparsity problem caused when users rarely post, and the static nature of information in traditional TRS. Bao et al. [2] provided a comprehensive survey of TRS that use location-based data in social networks, but do not relate any of these to support strategic decision-making by DMOs. Cheng and Edwards [9] used visual analytics on data sourced from Sina Weibo (the "Chinese Twitter") to provide destination managers insights into the effect of travel news on the attitudes of potential Chinese consumers. Marine-Roig and Clavé [47] proposed a method composed of five stages to gather and analyse big social data and images; the five stages are as follows: destination choice, web-hosting selection, data collection, pre-processing and content analysis. Although their study did not involve the development of any new analytics tool, their work is very pertinent within the context of the design of innovative analytics solutions in smart TD management. These various studies point to the underexploited potential for social media data to inform the DMO's strategic decisions [36].

2.3 Analytics in TD management

TDs may be considered as complex products with various tangible and intangible elements [5]. The tourism literature contains many accounts of previous attempts to identify tourist interests to support DMO's decision making. For instance, Mehmetoglu [48] attempted to identify popular tourist activities for the management strategy development. Zbuchea [76] examined tourists' cultural activities (such as visits to parks, heritage sites, museums and theatres), whereas Zillinger [78] focused on shopping activities. This information is useful for destination marketing, and services such as transportation can be better planned to meet the actual needs of tourists. An issue with the existing approaches to tourist behaviour analysis is that DMOs usually predetermine what should be examined, which may leave out other important visitor interests. Thus, DMOs have, to date, been unable to form an accurate picture of what activities visitors have *actually* been involved in. For many TDs (typically with a wide variety of different attractions), this information is crucial. In addition, traditional approaches to information gathering for TD management and planning purposes have previously relied heavily on surveys and questionnaires. This approach is time-consuming and not particularly effective. DMOs still face major difficulties in finding accurate answers to the following critical questions: What attracts tourists when visiting a destination? What locations do tourists visit in exploring a destination? What are the tourist's personal experiences at each of the visited attractions? What, at a fine-grained level (e.g. broken down by market segment, origin or age), does future tourism demand look like? By making use of big data, a DMO could obtain comprehensive insights on tourists' activities, their experiences and personal reflections. With regard to the determination of tourist preferences in TD management, Surugiu and Surugiu [62] highlighted the need for destination managers and entrepreneurs to use technological innovations, particularly social media, for collecting information on specific trends of interest and disseminating brand messages to potential visitors. Some previous studies, related to analytics solution development for TD management, are detailed in Table 1.

***** Please Insert Table 1 here*****

Most of the aforementioned studies attempted to propose analytics solutions for TD management using geographical data, but focused mainly on spatial aspects of tourists' locations or movements. These studies do not provide insights into the context and tourists' personal experiences at locations of interest, which is an essential prerequisite to better decision making in TD management. Although Wang et al. [72] commented on China's "smart tourism destination initiative" to suggest that connected tourists can share destination information with other tourists and service providers through apps linked to social media, none of the prior studies directly meets DMO's needs for strategic decision support. Moreover, detailed information at the individual tourist level is useful in developing a finer-grained segmentation of future tourism demand, for infrastructure development, and for service allocation and budgeting. The purpose of this study is, therefore, to outline a solution method for analysing social media big data, which can provide a comprehensive insight into tourists' behaviour and better predict future tourism demand, to support the decision-making of destination managers in the context of smart TD management.

3. Methodology

This section describes how DSR methodology is employed as a research strategy for designing, developing and communicating the proposed big data analytics solution as a design artefact, specifically, a method. The details on data collection and processing are also included in the section for the representations of theoretical and practical implications of the design. The evaluation approach is also discussed in this section.

3.1 Approaches

This research follows in the tradition of Hevner et al. [25] and Gregor and Hevner [23], in targeting a deeper understanding for the enhancement of organisational capabilities (in particular, a DMO's ability to make more informed strategic decisions) by developing a more powerful IT solution artefact. The adopted research methodology is modelled on the framework proposed by Hevner et al. [25], which conforms to seven guidelines covering three broad project phases (described in Table 2): identifying business problems and artefact types; artefact creation and evaluation and, finally, research contributions of the artefact and communication of results.

March and Smith [46] argued that design research can produce four types of artefacts: constructs, models, methods, and instantiations. In our study, we design a method as artefact, consisting principally of a set of algorithms intended to address current shortcomings in TD management decision support including the need for an improved understanding of tourists' interests and locations visited, and the need for better tourism demand prediction.

Our description is practically guided by Gregor and Hevner [23] in relation to explicating the level of artefact abstraction and knowledge contribution within their recommended publication structure.

Hevner's et al. [25] seven guidelines (Table 2) provide useful (but not purely prescriptive) criteria generally for defining a DSR study problem space, specifying a design-based solution artefact, implementing the design solution, evaluating the design artefact and communicating study details and results. To achieve our design goals, we grouped the guidelines into three phases for the following purposes: (1) determination of the relevant problem and design artefact required; (2) development and evaluation of the artefact; and (3) dissemination and knowledge creation of the research.

***** Please Insert Table 2 here*****

3.2 **Data collection and processing**

This work uses geotagged photo data publicly available on the photo-sharing site, Flickr. Those photos were taken by users along their travelling path using GPS-enabled photo capturing devices that automatically record geographical information. The photos and their associated metadata can be extracted using Flickr's Application Programming Interface [64]. For TD management, we can define the region, from which we want to extract data, by using a bounding box, whose coordinates are referenced by lo_{min}, la_{min}, lo_{max} and la_{max} for minimum longitude, minimum latitude, maximum longitude and maximum latitude, respectively. In addition to geographical data, temporal information such as photo taken date and time is also recorded automatically and stored in the photo tag. We can define the photo taken period by two parameters t_{min} for earliest time and t_{max} for latest time. Only photos taken within the defined region and time period are returned.

As mentioned earlier, the proposed method for geotagged photo data processing comprises four techniques, the details of which were described in the subsequent sections, as follows: (1) textual metadata processing; (2) geographical data clustering; (3) representative photo identification and (4) time series modelling.

3.3.1 Textual Metadata Processing

The textual metadata of photos often contain specific keywords, which may reflect certain priorities or tourists' interests and motivations when taking photos. Such textual data is normally unstructured, which is not suitable for the analysis without some form of pre-processing. We employ a powerful text processing tool named General Architecture for Text Engineering (GATE) [21]. GATE [21] provides several language databases, including an English lexicon, containing a comprehensive list of vocabulary terms for descriptions of interests.

Suppose there is a photo data set P, in which each photo p_i contains the metadata of its tags, title and description and is denoted as $t^{(p_i)}$. Each metadata construct $t^{(p_i)}$ is first loaded into a text tokenistic algorithm, wherein the stream of text is broken into words, phrases, symbols or other meaningful elements called "tokens". A filter is applied to the tokens to normalise all letters to lowercase, and to remove elements such as symbols and numbers. The remaining tokens are input into a stemming process to reduce inflected words to their stem, base, or root form. It is assumed that the English vocabulary of noun type is used to refer to entities of interests (e.g. street, building and tree). A list of stemmed nouns appeared in the data set is constructed, and is denoted as $S = \{s_1, s_2, \ldots, s_m\}$. The type of words such as nouns, verb or adjective can be determined based on a set of tags associated with each word in the English lexicon. A binary vector $\mathbf{b}^{(u_i)} = \{b_1^{(u_i)}, b_2^{(u_i)}, \ldots, b_m^{(u_i)}\}$ is then constructed for each user, where $b_j^{(u_i)}$ takes the value of 1 if s_j appear at least once in the textual metadata of the photo collection belonging to user u_i; or 0 otherwise. Let U denote the total number of users in the collected data set, and $C(s_j)$ denote the count of the vector $\mathbf{b}$, whose value is $b_j = 1$. The degree of interest of each stemmed noun $s_j \in S$, reflecting the degree of tourist interest, is evaluated by a support value:

$$support(s_j) = \frac{C(s_j)}{U} \tag{3.1}$$

A user predefined support threshold β is used to measure the significance of the nouns in the data set. If a noun s_j, satisfies $support(s_j) \geq \beta$, that noun is selected into a tourist interest candidate list; otherwise, it is removed. As a result, a list of interest candidates is automatically constructed from the textual metadata. A TD researcher can inspect the list to identify potential tourist interests for the subsequent analysis.

3.3.2. Geographical Data Clustering

This stage aims to identify popular location(s) for each of the identified tourist interests. Suppose $\hat{P}$ is a collection of photos whose textual metadata contains a keyword indicating a specific interest of a tourist. A clustering technique, named P-DBSCAN [34], is applied to the geographical data of $\hat{P}$ to identify popular areas of interest. It considers both the number of photos and the number of tourists, which ensures that the identified locations actually have many tourists who have visited for a particular interest. The advantage of P-DBSCAN has been shown in recent studies to identify popularly visited location by tourists [45; 38]. The geographical data of each photo p_i is referenced by value pairs, $< lo_{p_i}, la_{p_i} >$, for longitude and latitude, respectively. Distance between two photos p_i and p_j on the Earth's surface is computed [49] and denoted as $D(p_i , p_j)$. Let r be a neighbourhood radius. The neighbourhood photo $N_r(p_i)$ of a photo p_i is then defined by:

$$(3.2) \qquad N_r(p_i) = (p_j \in \hat{P} , O(p_j) \neq O(p_i) | D(p_i, p_j) \leq r)$$

where $O(p_j)$ is an ownership function to specify the owner of photo p_j. Let $|N_r(p_i)|$ be the number of owners of the neighbouring photos $N_r(p_i)$, and α be an owner number threshold. Photo p_i is called a core photo if $|N_r(p_i)| \geq \alpha$. At the beginning of the clustering process, all photos are marked as unprocessed. For each photo p_i, if it is a core photo, it is assigned to a cluster c and its neighbours assigned to a queue to be processed next; otherwise, it is discarded. Each of the neighbouring photos is then processed and assigned to the current cluster c until the queue is empty. The process is iterated for the rest of the photos in $\hat{P}$, and the result is a set of clusters $C = \{c_1 , c_2 , \dots\}$. The geographical coordinates of the clusters are then examined to determine the location of tourist interests and their spatial extent.

3.3.3. Representative Photo Identification

Given a specific location, tourism managers are interested in identifying the most representative photos for each tourist interest. This allows insight into tourist's personal experience to be obtained, with implications for developing promotional material and destination iconography. In our artefact, representative photos are defined as those photos whose contents appear most frequently in a set of photos. Our representative photos identification is carried out in two steps: *Visual Content Representation* and *Kernel Density Estimation*

Visual Content Representation: Feature descriptors for local regions are used as powerful cues in automatic natural scene recognition [70] and are robust to occlusions and spatial variations [69]. We adopt Speeded-Up Robust Features (SURF) [3], an advanced feature descriptor, to represent photo content. A popular approach to represent photo content using local region descriptors is to represent each image as a bag of visual words [39; 40]. SURF descriptors are first extracted for a large set of local regions extracted from a set of random photos. K-means clustering is applied to construct a visual word vocabulary. Visual words are defined as the centre of clusters, and the value of *k* determines the number of visual words available. For a new photo p_i with a number of local regions, the SURF descriptors are extracted and then vector quantised into the visual words for the vocabulary. Each photo is then presented as a bag of visual words, denoted as $\mathbf{w}^{(p_i)} = \{w_1^{(p_i)}, w_2^{(p_i)}, \dots, w_k^{(p_i)}\}$. The value of each element $w_j^{(p_i)}$ is the number of times the visual word $w_j^{(p_i)}$ appears in photo p_i. Values of w_j are varied depending on the content in photos, which helps to characterise the visual content of the photos.

Kernel Density Estimation (KDE): KDE is a non-parametric method to estimate the probability density function of a random variable [63]. Let $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_\mathrm{n}\}$ be a sample set of d-dimensional random vectors drawn from a common distribution described by the density function f. The multivariate kernel density at each point $\mathbf{x}$ is estimated as:

$$\hat{f}_{\mathbf{H}}(x) = \frac{1}{n}\sum_{i=1}^{n} K_{\mathbf{H}}(\mathbf{x} - \mathbf{x}_i) \tag{3.3}$$

where $\mathbf{H}$ is a $d \times d$ symmetric and positive definite matrix, which acts as a smoothing parameter. $K_{\mathbf{H}}(\mathbf{x} - \mathbf{x}_i) = |\mathbf{H}|^{-\frac{1}{2}} K\left(|\mathbf{H}|^{-\frac{1}{2}}(\mathbf{x} - \mathbf{x}_i)\right)$ is the kernel, a non-negative function that integrates to one and has mean zero. The choice of the kernel function $K_{\mathbf{H}}(\mathbf{x} - \mathbf{x}_i)$ is not crucial to the accuracy of kernel density estimators [7].

In practice, multivariate kernel density estimators in more than three dimensions suffer from the curse of dimensionality [51]. A higher dimensional space is sparsely populated by data points, with very few neighbouring data points to any value $\mathbf{x}$. It is thus necessary to reduce the dimensionality of the data points for the bag of visual words features, while still preserving the similarity or distance between them. We thus apply the Multidimensional Scaling (MDS) technique [6] to the bag of words feature. Let $\delta_{i,j} \approx ||\mathbf{w}^{(p_i)} - \mathbf{w}^{(p_j)}||$ be the Euclidean distance between the bag of word features of photos pair p_i and p_j. The goal of MDS is to find vectors $\mathbf{x}^{p_1}, \mathbf{x}^{p_2}, \dots \in R^d$ such that $||\mathbf{x}^{(p_i)} - \mathbf{x}^{(p_j)}|| \approx \delta_{i,j}$, where the chosen value of d is small (2 or 3). After the application of the MDS process, each bag of words $\mathbf{w}^{(p_i)} = \left\{w_1^{(p_i)}, w_2^{(p_i)}, \dots, w_k^{(p_i)}\right\}$ having k-dimensions is transformed into a low-dimensional vector $\mathbf{x}^{(p_i)} = \left\{x_1^{(p_i)}, x_2^{(p_i)}, \dots, x_d^{(p_i)}\right\}$ having d dimensions. Given the reduced dimensional feature $\mathbf{x}$, we then identify the probability density of each photo according to Eq. 3.3. The top photos with the highest probability densities are returned as representative photos. The general theme of the photo collection for each feature of interest can be easily identified by examining the small numbers of representative photos.

3.3.4 Time Series Modelling

Given a geotagged photo data collection, time series data are constructed by counting the number of tourists according to months. The trend of the time series can be estimated using a parametric approach because it produces smooth trend curves representing the overall tendency, and allowing for future trends to be computed for prediction purposes. Popular fitting functions include linear, exponential and quadratic types, whose description is provided in [12]. The choice of fitting function can be determined using the mean absolute error (MAE), a commonly used measure of model performance in time series analysis:

$$MAE = \frac{\sum_{t=1}^{N} |O_t - E_t|}{N} \quad (3.4)$$

where O_t and E_t are the original time series data and estimated trend, respectively. N is the total number of data samples. It should be noted that in our study, the use of MAE is to select the most appropriate model for trend estimation rather than to predict an actual value of the time series. A smaller MAE indicates a better model for our purpose of analysis. Besides the trend, we can reveal seasonal patterns using a time series decomposition technique. The seasonal component is obtained by subtracting the estimated trend E_t from the original time series O_t. By assuming that seasons are months, seasonal mean values are computed as the average of seasonal components for the same month according to years. Figure 1 shows an example of time series decomposition. The trend was modelled using a quadratic function (Figure 1.a), and seasonal means are shown by the red line, whose values are computed by the average of seasonal components for each month (Figure 1.b).

4. *** Please Insert Figure 1 here***Artefact description

The analytics artefact comprises four techniques, the details of which were described in Section 3.3. The techniques are (1) textual meta-data processing, (2) geographical data clustering, (3) representative photo identification and (4) time series data modelling, and these are represented as a conceptual framework in Figure 2. In brief, textual metadata processing aims to find specific keywords that reflect certain objects of interest to tourists (as they took photos). A list of candidates is constructed from the data collected, and this can be used to identify topics (e.g. locations, attractions) of tourist interest. For clustering geographical data, we used an algorithm called P-DBSCAN [34], which identifies areas of high photographing activity, using information both on the number of tourists supplying photos and the number of photos uploaded to find clusters in popular tourist locations. This algorithm ensures the identified "attractive places" are decided by the tourists' own choices of photographic subject, and is analysed at fine-grained levels, allowing local, domestic and various groups of international tourists' distinctive cluster patterns to be discerned. The third technique is to identify representative photos (e.g. the photo subjects that most frequently appear) for each tourist interest that provide insights into tourist's own experience and interests. The representative photo identification stage is carried out in two distinct steps: visual content representation and kernel density estimation as described in Section 3. Finally, the time series data modelling technique aims to predict future tourism demand and reveal seasonal travel patterns for future planning and decision-making.

***** Please Insert Figure 2 here*****

The four techniques are combined together in our solution artefact to process and analyse different types of data (textual tags, geographical tags, photo content and time), to provide deeper and more comprehensive insights into tourist behaviours and perceptions than previous solutions developed for TD management. For instance, the solution of Supak et al. [61] focused on accommodation locations rather than the wider range of actual tourist activities at destinations. The GIS system proposed by Li et al. [41] can analyse tourist activity but is incapable of providing detailed information on tourist interests and perceptions. The cloud-based analytics application, developed by Zhou et al. [77], was based on geotagged photos, and this is relatively close to our solution. However, their system was could handle only textual tags and geotags, but was unable to process visual information contained in photographs or detect time-based trends. In addition, the clustering technique used in their solution consider only the photos taken by themselves but not the number of visitors, and this, as Kisilevich et al. [33] argued, provides a less-accurate indication of popularity. Most importantly, no existing solution has the capability to predict future demand for the range of destination attractions. Our proposed method is designed to perform the prediction of tourism demand based on time series modelling in the fourth stage. A DMO is not only able to have a detailed insight into tourist interests but is also able to estimate the future trends and seasonal effects for better planning and strategic decision-making. The effectiveness of our solution artefact is demonstrated using the case of a major tourist destination, Melbourne, Australia, in Section 5.

5. Evaluation and case demonstration

Hevner et al. [25] offered five approaches for evaluating design artefact: observational, analytical, experimental, testing and descriptive. We adopted the descriptive approach as we used case data (Melbourne) as a representative destination for tourism, which can be validated against justifiably accepted knowledge and independent tourism statistics. The experimental approach was also partially adopted; in that, qualities of the proposed artefact were evaluated through internal assessments of comparative quantitative settings and fitting models. By referring to ongoing stakeholder evaluation during iterative development, validity and utility considerations were addressed throughout. The algorithms and techniques used, namely P-DBSCAN and SURF [3], are stable and robust and have been independently shown to be superior to alternatives in the literature already cited.

The following section demonstrates the practical application of the proposed method through an expository illustration using tourists' social media data for Melbourne, Australia. Melbourne represents a major destination, serving both domestic and international markets, and, receiving 2.4 million international visitors in the current year to March 2016 and 8.4 million domestic visitors in 2015 [66]. This generates a lot of social media content. The geotagged photo data were extracted and processed using the framework discussed in the previous section to identify tourist interests, locations, representative photos and to support demand forecasting. Description and analysis of the results are provided, followed by a discussion of practical implications.

5.1 Data description

The geotagged photo data set used in this study was collected from Flickr using its API. A bounding box, with coordinates, $lo_{min} = 144.40882$, $la_{min} = -38.222732$, $lo_{max} = 145.578864$ and $la_{max} = -37.461429$, was designed to cover the entire geographical area of Melbourne, as indicated on Google Maps (www.google.com.au/maps). The photo timeframe was 5 years, covering the period from 2011 to 2015. In total, 238,290 photos were collected from 7392 tourist's accounts. Photo metadata were extracted, including geotags, textual tags, titles, descriptions and UserIDs. The actual photos were downloaded, using ‘medium’ size (as defined within Flickr), which is adequate to display content sufficiently clearly for subsequent processing stages while reducing computing costs.

In addition to an overall analysis of tourist interests, our solution artefact also predicts the demand for different demographics groups. The geographic origin of each user was retrieved from Flickr based on the UserID. Melbourne residents were treated as local tourists, whereas tourists coming from other parts of Australia (domestic tourists) were labelled as the Australia group. International visitors were grouped based on their home continent. Most international tourists came from Asia, Europe, North America, and thus, only these groups were considered in this analysis. As provision of resident location is not essential when creating a Flickr account, many users did not provide such information. In total, 2550 tourists were identified with location of residence as shown in Table 3. Although this number of tourists is less than that of the original data set, it is sufficient to extract trend and seasonal patterns for demand forecasting. Here we noticed that local tourists appeared to take many more photos than tourists from other locations, with more than 46 photos per tourist. Tourists from other groups took around 16 photos each on average. This is probably because that tourists from other places are limited by the time constraints of their trips, whereas local residents have a longer time to explore, which results in more photos being taken.

***** Please Insert Table 3 here***5.2 Tourist interest identification**

The entire photo collection was used in this experiment. Textual metadata attached to the photos that were processed using the method discussed earlier (Section 3.3.1). Some photos did not have tags, title or description as users did not tag or provide a description when uploading. These were treated as missing data.

Using *MATLAB* as the computing environment, we first evaluated the performance of the textual processing technique with different support thresholds β, ranging from 0 to 0.1. The number of interest candidates for different β values is shown in Fig. 3a. The numbers of interest candidates drop dramatically as the β increases from 0 to 0.01, and then decreased slightly. With $\beta = 0$, the system returned all the entries in the noun list. When $\beta = 0.1$, very few nouns remained in the returned list. The aim of this processing stage was to identify the most popular interests of tourists; therefore, the support threshold β was set to 0.05, which returned 52 candidates. The candidate list was refined by removing words such as “Melbourne”, ”Victoria”, ”Australia”, which have no meaning in the context of Melbourne-specific tourist interests. In addition, if descriptive words were synonyms (e.g. “sunset” and “nightfall”), only the word with the highest support was kept. The refined list of tourist interest candidates consisting of 17 items ranked from the highest to lowest support (Fig. 3b).

***** Please Insert Figure 3 here*****The results indicated that Melbourne visitors are interested in built infrastructure such as street, bridge, tower, house, station and architecture (It is notable that Melbourne has significant Victorian era architecture, as well as the more modern Federation Square at its central area around Flinders Street and Swanston Street). Natural scenes also received substantial attention and that included sunset, river, tree, beach and sky. Other attractions of interest included art, park, garden, people, car (possibly tramcar) and shop.

5.3 Location of interest

From the list in Fig. 3a, relevant photos for each interest candidate were extracted. Each photo collection was then input into the geographical data clustering process as presented in Section 3.3.2. The neighbourhood radius r is set to 0.002, which is equivalent to approximately 150 m. The minimum owner α is set to a value of 10% of the total number of tourists in each photo collection. An advantage of our approach is the ability to integrate geographical data into GIS services such as Google Maps. The resulting clusters were inspected to determine the locations and geographical extent of the interests. Figure 4 shows the clusters for tourists’ interests in Melbourne. The clusters are represented by the coloured dots on the satellite images. The clusters for different interests are visualised with the same colour to make it convenient for cluster location identification purpose, and then an interest profile is constructed based on the identified locations.

***** Please Insert Figure 4 here*****Figure 4 indicates that most popular area is the Melbourne Central Business District (CBD), as most clusters were found in this area. Further afield areas such as St Kilda Beach and Brighton Beach were also identified as popular areas for tourist interests. The image on the right is a zoom-in on the CBD area for the detailed analysis. We can see that the major clusters are at the city centre along Swanston Street, Flinders Street, and some are along the river bank. Some clusters are also found in the botanic gardens nearby.

We inspected the clusters for each interest separately to identify their specific locations. Table 4 summarises the locations of interests. The columns indicate the interests, while the rows indicate the specific locations. A tick means that tourists have a specific interest at that specific location. We can see that some locations have multiple interests such as Melbourne Central, Flinders Street and Princes Bridge, as shown with the high values (5 or more) for interest count. These are in fact verifiably the most iconic locations for tourists when visiting Melbourne. On the other hand, some locations have unique interests such as Brighton Beach, Southern Cross Station, Parliament House, Fitzroy Garden, Royal Botanic Garden and the bridges (Kings, Seafarers, Webb). In addition, some interests are found at different locations. For example, the art interest can be found at Union Lane, Hosier Lane and South Bank.

***** Please Insert Table 4 here***5.4 Representative photo analysis**

To discover tourists' personal experience of specific interests, the system can identify the representative photos using the visual content processing approach, as introduced in Section 3.3.3. Photo visual content is extracted using Maximally Stable Extremal Regions detectors [52] and SURF [3] descriptors. The vocabulary's size was set to $k = 400$ words, generated from around 200,000 local regions from a set of random images in the photo collection. A small number of sample images and visual words have been shown to be sufficient for visual word construction [17], whereas higher numbers of visual words do not have a significant influence on performance [55]. A bag of visual word features was generated for each photo. Those photos relevant to each interest at a specific location were grouped together as a collection of photos, from which representative photos were identified.

The MDS technique was applied to each collection of photos to reduce the dimensionality of data points to $d = 3$, which is sufficient for Kernel Density Estimation. The probability densities for the photos are estimated using the kernel (e.g. normal distribution) with default smoothing parameters as suggested in Bowman and Azzalini [7]. Top photos with highest probability densities are returned as representative photos.

Figure 5 shows sample representative photos for *art* and *sunset* and their locations. The art photos at South Bank show artefacts displayed indoors. The art photos at Hosier Lane and Union Lane appear to be the graffiti painted on the building. Sunset photos show different scenes at different locations, a sea scene at St Kilda Beach, and a building with river at Flinders Street.

***** Please Insert Figure 5 here*****We examined the representative photos for the other interests at different locations, such as people, street, car, architecture, tree, river and sky. These show general scenes, which we do not report in this paper. However, some scene clusters were found for other interests, as shown in Fig. 6. Findings of interest include the following observations:

- Tourists are interested in taking photos of the design and structure of the Webb Bridge and the Seafarers Bridge, as shown in Fig. 6a and 6b. The photo taking position is usually on the bridges. On the other hand, tourists usually take photos of Princes Bridge with river scene at a far distance (Fig. 6c).
- Photos at Eureka tower are usually taken from outside with the sky in the background (Fig. 6d). In contrast, tower photos at Melbourne Central are taken inside, with the ceiling in the background (Fig. 6e).
- Photos, which are taken at the gardens in Melbourne, usually focus on nature scenes of trees and flowers, especially from a close distance as in Fig. 6f for Carlton Garden. However, garden scenes at South Bank focus more on human activities such as the 'fire' attraction shown in Fig 6g.
- Contrasting scenes were found for photos of stations. Tourists are interested in the internal area of Southern Cross Station (Fig. 6h). Photos at Flinders Street Station, a major landmark and heritage building, focus on the external area of the station (Fig. 6i).

***** Please Insert Figure 6 here***5.5 Tourism demand forecasting**

This section describes the building of time series models for predicting future tourism demand for Melbourne. The monthly arrivals of tourists for Australia, Asia, Europe and North America groups were counted for 2011–2015. Parametric fitting models were applied to the time series data for trend estimations. As the selection of fitting model is dependent on the specific application, we evaluate the performance of the most popular models (*linear, quadratic,* and *exponential*) on our data set. The data for 2011–2014 was used as training data, whereas the data for 2015 was reserved for testing. MAE was used to evaluate the performance on the test data, as shown in Table 5. A lower MAE value indicates a better model. The lowest error value for each group is underlined. The quadratic model appears to be most suitable for the Australia and Asia groups, as indicated by the lowest MAE. Linear and exponential models outperformed the Quadratic model for the Europe group, though the exponential had a slightly lower error. The linear model is the best for the North America data; however, the performance of all three models was relatively close.

***** Please Insert Table 5 here*****On the basis of the above evaluation, we used the quadratic model to estimate and predict the trend for the Australia and Asia groups, the exponential model for the Europe group and the linear model for the North America group. Figure 7 shows the original data and the estimated trend. There was a slight decrease in the trend of the Australia group from 2011 to 2014, which then remained stable in 2015 and may increase in 2016 (Fig. 7a). For the Asia group (Fig. 7b), there was an increasing trend until 2013 with more visitors to Melbourne, but then a decrease from 2014. The number of visitors is projected to continue to decrease gradually in 2016. Slight decreases in tourism demand were found for the Europe and North America groups (Fig. 7c and Fig. 7d), and these were estimated to continue reducing in 2016. It should be noted that the predictions only estimate the future trend of tourist demand, not the actual number of tourist arrival, as the model was not built on the true statistics of tourist arrivals. However, the method provides a fine-grained analysis to complement and qualify the estimates from aggregated figures projected from general surveys and official statistics.

Besides identifying trends, tourism managers need to know the seasonal patterns of tourist arrivals for strategic planning and decision-making. Seasonal mean models for the 5-year data set were computed using the time series decomposition method described in Section 3. No clear seasonal pattern was found for the Australia group, as shown by the fact that mean values are relatively close to 0 (Fig. 8a). Asian tourists are more likely to visit Melbourne in February, and least likely in June (Fig. 8b). This historical pattern has been independently established for Chinese visitors to Australia (China is Australia's largest inbound market by expenditure and visitor nights) [65], and helps validate the utility of our analysis. Similarly, a clear pattern was found for the Europe group (Fig. 8c): they are more likely to visit Melbourne from December to March, but less in the middle of the year. A slightly different pattern was found for the North America group (Fig. 8d): the high peak time for this group is from January to March and in November; the low peak time is from April to September.

***** Please Insert Figure 7 here*****

***** Please Insert Figure 8 here*****

6. Discussion

In this paper, we have described a method for analysing social media big data for strategic decision support by DMOs. To manage a TD effectively, DMOs need to have a comprehensive understanding of tourists' interests, visited locations, tourists' personal experience and be able to predict future tourism demand [75]. Data generated by social media provide details of individuals' experiences and expression with time-stamped, demographic and evidence-based insights that contribute to the DMO's understanding of market perceptions and behaviour.

Traditional analytics methods and specialised techniques are inadequate for analysing the huge and unstructured social media datasets that hold diversified data formats, and the growth of this data is massive. Previous studies have developed analytics solutions for automatically detecting tourists' behaviour and city preferences (e.g. [77]) but have not been designed for visual photo content and metadata processing to capture tourists' experiences. In addition, they are incapable of making predictions necessary for a DMO's fine-grained strategic decision-making needs. Our approach performs tourism demand prediction based on temporal information extracted from social media data, rather than using data from surveys and questionnaires as in traditional approaches (e.g. [1; 44]). Equally location-based analytics are just beginning to emerge in GIS design theories to explain and contextualise spatial analyses and our research contributes to nascent design theory here too.

By adopting the established principles of DSR as one of the eminent information systems design methodologies, we have gone beyond existing big data analytics methods in automatically detecting tourist's interest in objects, particular spots and clusters, along with detailed insights on collective behavioural and nationality profiles. Our study has developed an IT artefact in the form of a general method for generating meaningful information and predictive insights from geotagged photos. Results show that our solution method (as IT artefact) can detect key patterns and trends for a representative major tourist destination with the details relevant to strategic DMO decision-making.

The performance of our solution artefact resulted from a number of specific algorithms and showed stable and usable results in both spatial and numerical forms. On the basis of the findings of tourist's interest and locations, DMOs could develop targeted marketing materials that cover the wide range of locations of interests. For instance, the Melbourne City DMO could highlight the availability of Art, Botanic Garden and Architecture attractions for tourists visiting the Southbank area. City tours could be designed to more accurately reflect tourists' interests and enrich their travel experience, for example, by suggesting tourists visit St Kilda Beach for a sunset experience and associated photographs.

The representative photos provide insight into tourists' perspectives and perceptions. DMOs could show photos of bridge structures when designing websites or marketing material for the Webb Bridge and Seafarers Bridge (which have intrinsic architectural interest), whereas a river scene could be shown for the, more traditional, Princes Bridge. There is an increasing trend for domestic tourists to visit Melbourne, and they also have a wide range of interests. DMOs could develop differentiated travel packages that suit the demands of local and interstate markets through insights emerging from the application of the method. Parts of the method previously have been detailed to academic audiences (e.g. through academic workshops), and the complete artefact has also been informally outlined to both academic and industry audiences, and this helped to improve the design iteratively and to ensure the relevance to the actual decision-making processes of DMOs. In addition, we have successfully tested the artefact using a number of experiments (although only the results for Melbourne have been presented in this paper for the expository purpose of demonstrating an instantiation). Our illustrative case suggests that the proposed method can work in any city (or analogous tourist destination) if sufficient geotagged photos/records are available. For example, using the data for Sydney (we found 333,500 geotagged photos from 9841 users on Flickr for 2011–2015), similar experiments were performed and revealed tourists' behaviour and interests, and this validated the utility of the proposed artefact for other DMOs. The near-term generalisability of the artefact applies to other destinations and their management and promotion applications, but there seems to be no reason why the method cannot be adapted to address different applications and domains in the longer term. For example, travel route recommendation systems could be developed, using geolocation data to suggest, and exhibit nearby attractions that have appealed to other tourists or to suggest a particular visitation sequence given limited time. As geotagged photos are available globally, tourists' interests and behaviour could be analysed for inbound travel across different markets, as well as clustering lesser-known attractions or less-visited parts of a region, which DMOs have a responsibility to promote. Beyond tourism applications, in traffic management for example, geotagged public photos (e.g. from surveillance or dash cams) could be organised in sequential order to reveal travel patterns or to identify busy travel routes between destinations for public transport planning.

The limitations of the study largely concern the completeness of the collected data. Social media contains other sources of valuable, but unstructured data, such as tweets and videos. These can also potentially be mined to discern tourists' sentiments and interests. A second limitation is the profile of those posting photos: they may be assumed to be younger and tech-savvy. In time though, it is anticipated that older tourists will increasingly take photos and upload them to social media. A third limitation is that a single site, Flickr, was used as the data source. Sites such as Instagram, Snapchat, Facebook, Twitter and other blog hosts all support photo uploads, of which many are publicly accessible. However, some of these social media sites strip the metadata, or limit the time for which a photo is available, which restricts the use of the method for data from these sources.

7. Conclusion

We have presented a method to extract, rank, locate and identify meaningful tourist information from unstructured big data sets for supporting the DMO strategic decision-making. By analysing geotagged photos along with other related details, our method is applicable to different destinations and generated useful results, as illustrated for the case of Melbourne, Australia. We followed the established theory and methodological guidelines of DSR for the design, development and dissemination of the generated artefact; a method, one of the four types of design artefact recognised in the DSR literature in information systems. We utilised *MATLAB*, a numerical computing environment, together with Google maps, a desktop web mapping service, as the technical platform/environment to develop and evaluate the solution method.

For further technical enhancement to our proposed analytics method, advanced relevant algorithms will be utilised to improve the analysis capabilities. We noticed that Oku et al. [53] used Support Vector Machines (SVMs) for identifying tourism spot regions by estimating high-density spots. Our next study will incorporate machine learning approaches such as SVMs or Neural Networks (as explored in Qiu et al. [58]) to improve predictive capabilities and identification accuracy of tourism demand forecasting. We also believe that a fully functional social media analytics artefact for a target problem domain requires end-to-end design, capable of performing big data acquisition from social network sites, cleansing of noisy, inadequate and duplicated data, extracting relevant features and, not least, performing analytics. In the paper, we described our solution using a case demonstration. In future studies, we will continue to fine tune the solution artefact in conjunction with real decision makers, and more formally evaluate its usability and range of applicability. Another set of studies will examine non-city regional destinations, such as wine regions, and destinations with long-distance walking and cycling trails, driving tours and cruises. Although we have no reason to believe the method will not work unchanged for these cases, any fine-tuning will enhance the method's general utility.

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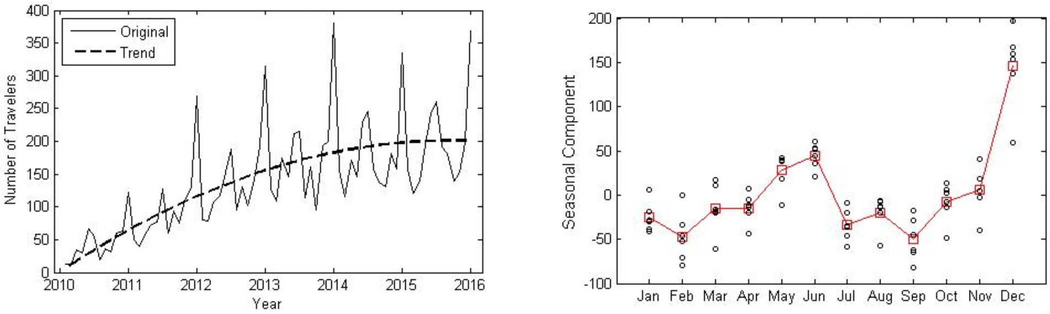


(a) Trend

(b) Seasonal Means

Figure 1: Time Series Decomposition Example

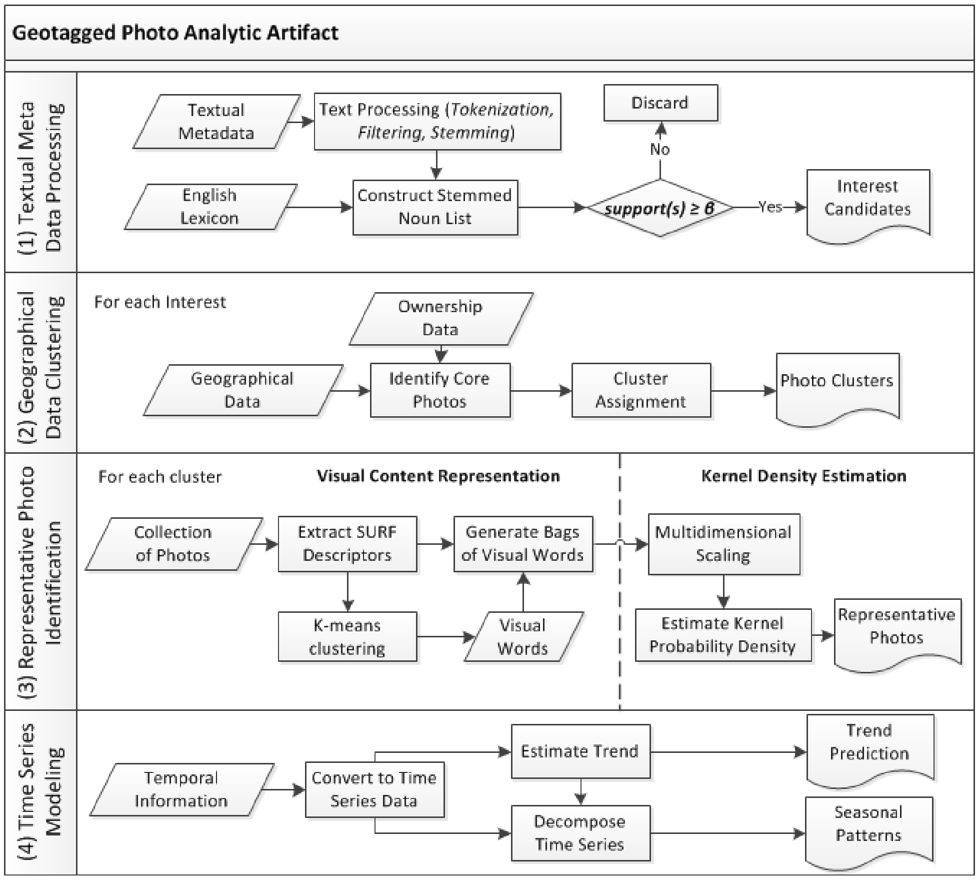
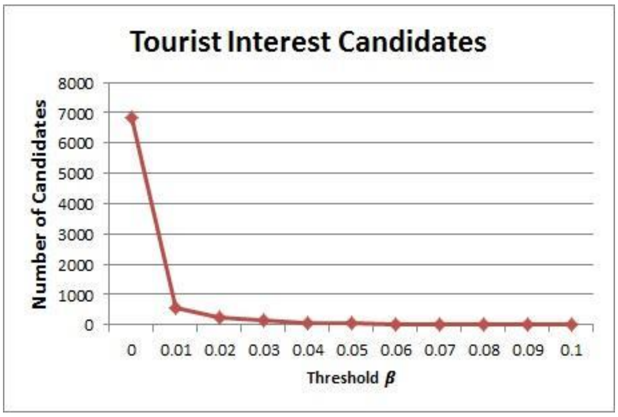
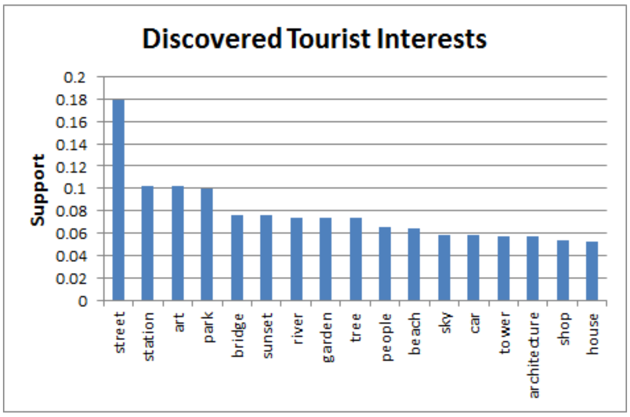


Figure 2: Conceptual framework of the proposed big data analytics





a) Number of Candidates with different β

b) Identified Candidates with $\beta = 0.05$

Figure 3: Tourist Interest Candidates

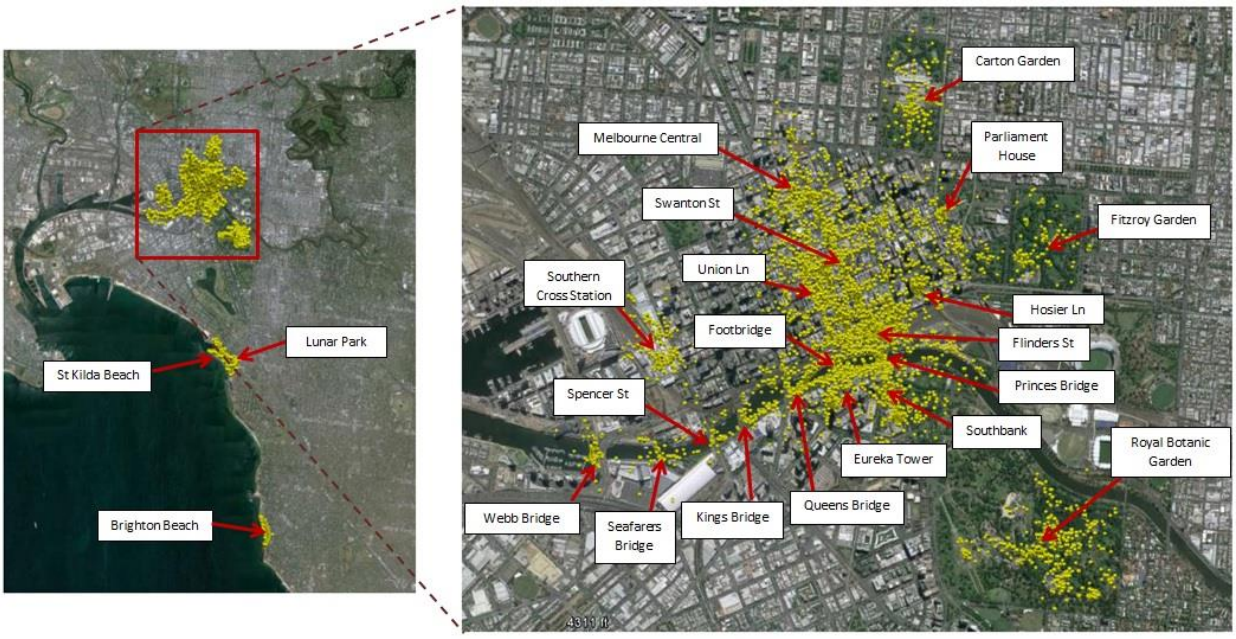
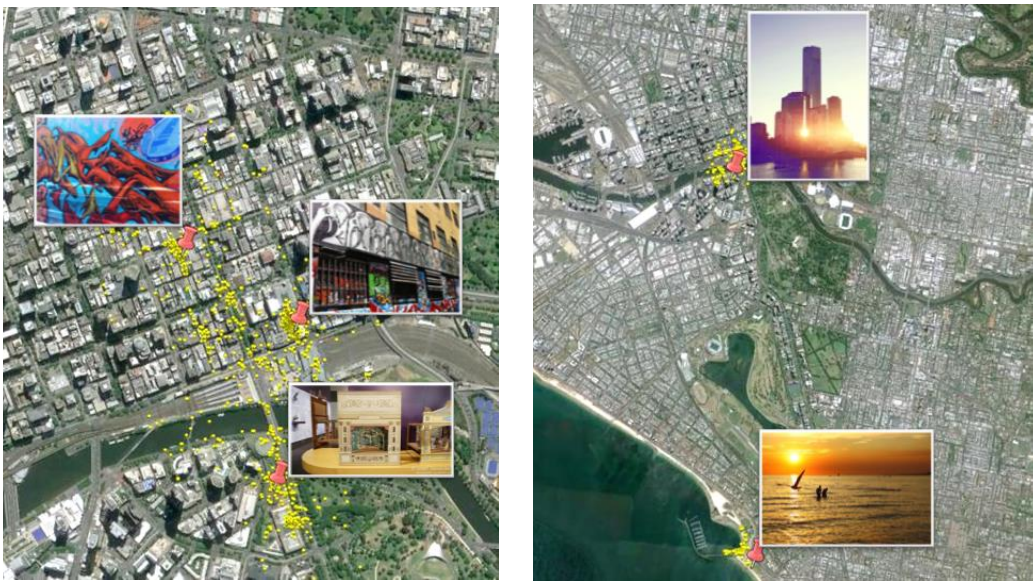
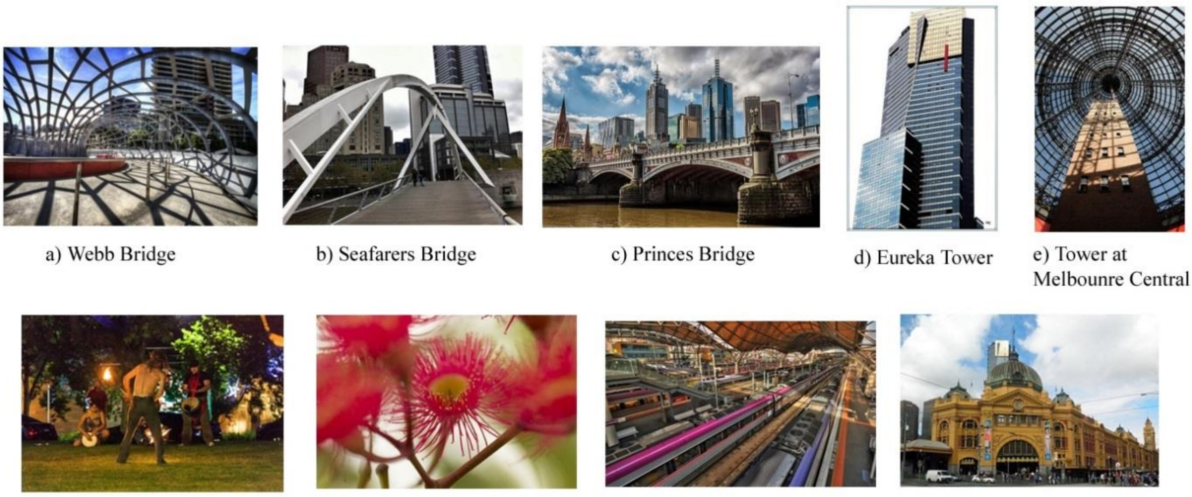


Figure 4: Clusters of Tourist Interests in Melbourne



a) Art b) Sunset

Figure 5: Representative photos for Art and Sunset Interests



a) Webb Bridge b) Seafarers Bridge c) Princes Bridge d) Eureka Tower e) Tower at Melbounre Central

f) Carlton Garden g) Garden at South Bank h) Southern Cross Station i) Flinders Street Station

Figure 6: Representative photos.

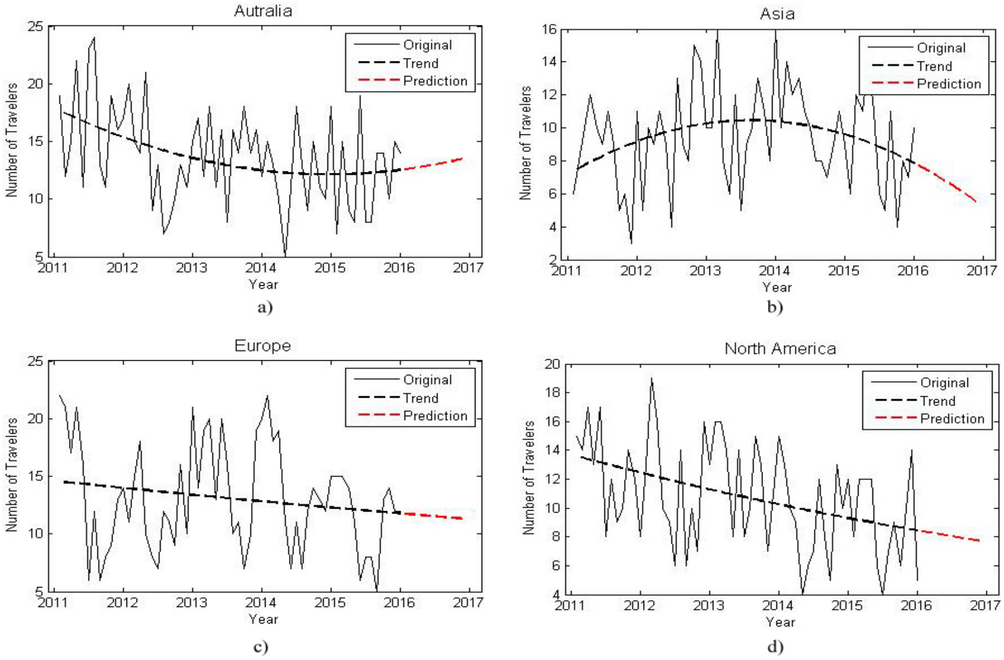


Figure 7: Trend Estimation

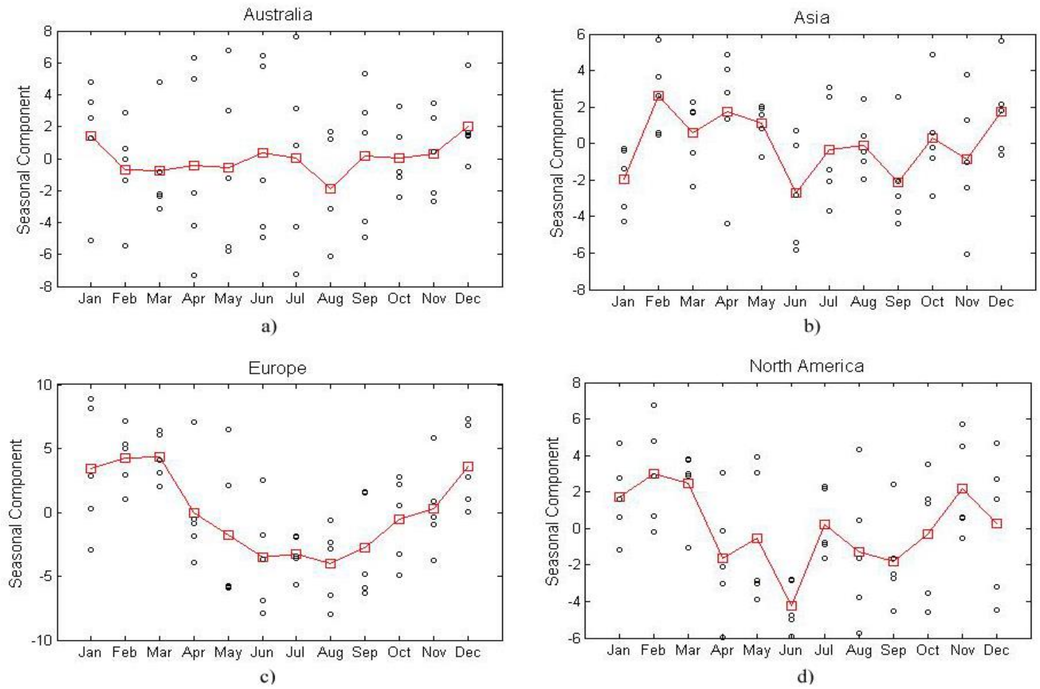


Figure 8: Seasonal Pattern

Table 1: Key studies: Analytics Solutions for TD Management

Sources	***Solution methods***	***Key theories***	***Types of big data***	***TD purposes***
Chua et al. [10]	Method of flow analytics	Trajectory mining technique to process the tweet data	Geotagged twitter data	Tourist flow and temporal details of destinations
Chancellor [8]	Method of extracting travel pattern	LCF (Lue, Crompton and Fesenmaier) five-pattern model [43] of recreational travel pattern analysis	Mobile interviewer collected data from visitors' stops	Travel pattern data for destination development
Fuchs et al. [18]	Business intelligence	OLAP (Online Analytical Processing) and ETL (Extract, Transform, Load)	Facebook, Youtube, and other e-reviews	Generate tourist-based knowledge in Sweden
Leung et al. [37]	Method of social media analysis	Traditional technique of trip diary	Tourist generated social media data (from six social media sites)	Identifying tourist movement in destinations (pre, during and post-Beijing Olympic games),
Li et al. [41]	Space syntax analytics	Space Syntax analysis following time series	GPS and location-based sensors (high-resolution video and picture)	Understanding of tourist space in China
Orellana et al. [54]	Method of data analytics	Computational movement analysis was used to detect movement	GPS based tracking data	Flows of tourists in recreational destinations

		suspension and generalized sequential patterns		
Oku et al. [53]	Method of identifying tourism spot	DBSCAN clustering and Support Vector Machine techniques are used to train and extract the spots	Geotagged twitter data	Identifying about spot (destinations) in regions
Supak et al. [61]	Geospatial big data analytics	GIS and open source web-mapping application	Federal and enterprise records of visitors data	For creating tourist demand model and market profiling
Zhou et al. [77]	Cloud-based analytics	Image clustering, cluster representation, cluster refinement and tracking, spatial analysis using cloud computing	Geo-tagged digital photo of Flickr and Instagram through Yahoo lab	Tourists' experiences of and preferences for particular tourist spots

Table 2: DSR study phases and guidelines [25, p. 83]

Our project phases	Utilised DSR Guidelines	Our artefact design
identifying business problems and artefact types	**Guideline 1:** Design as an Artefact.	The study has produced a big data analytics method designed to generate key decision support information for TD operational and strategic planning purposes.
	Guideline 2: Problem Relevance	DMOs worldwide must make strategic predictions. Most current DSSs are incapable of handling largely unstructured social media data, and the supporting processes (methods) for this purpose have also not been adequately detailed in the previous research. This is the essence of the research gap addressed by our DSR study.
artefact creation and evaluation	**Guideline 3:** Design Evaluation.	To demonstrate artefact utility, experiments have been conducted, coupled with a case scenario analysis using test datasets. Iterative development in consultation with representative stakeholders ensured ongoing evaluation and relevance.
	Guideline 5: Research Rigor.	The big data analytics artefact was constructed using proven mathematical modelling techniques and evaluated using fundamental and commonly accepted research methods (experiment and case study).
	Guideline 6: Design as a Search Process.	Mathematical modelling methods employed in other domains were adapted for use in this study. The design process was iterative to cope with much of the uncertainty inherent in the problem space (e.g. with TD management requirements) and to allow progressive and incremental development and evaluation.
Research contributions of the artefact and communication of results	**Guideline 4:** Research Contributions.	The algorithms and techniques produce clear and testable results. The sequence of complementary techniques produces a valuable analysis of big data directly relevant to strategic decision support. The experimental outcomes and case analysis have shown clear benefits and new approach to the target decision makers.
	Guideline 7: Communication of Research.	This study presents detail relevant to academic, management and technical audiences, and has been verbally presented in workshops during the development activities. That is how the artefact has been positively assessed for the relevance to their decision-making practices.

Table 3: Data Collections by Travel Groups

Group	No. of Tourist	No. of Photos	Photos Per Tourist
Local	895	41,675	46.56
Australia	422	6,558	15.54
Asia	338	5,189	15.35
Europe	481	7,831	16.28
North America	414	6,990	16.88
Total	**2550**	**68,243**	

Table 4: Tourist Interests by Specific Locations

	Attraction					**Infrastructure**							**Natural**					
	art	garden	park	people	shop	architecture	brige	car	house	street	station	tower	beach	river	sunset	sky	tree	**Interest Count**
St Kilda Beach													✓		✓			2
Brighton Beach													✓					1
Lunar Park			✓															1
Southern Cross Station											✓							1
Melbourne Central				✓	✓	✓				✓		✓						5
Swanston St				✓	✓	✓				✓								4
Union Ln	✓									✓								2
Carlton Garden		✓				✓											✓	3
Parliament House									✓									1
Fitzroy Garden		✓																1
Hosier Ln	✓									✓								2
Flinders St				✓		✓		✓		✓	✓				✓	✓	✓	8
Princes Bridge				✓			✓			✓				✓	✓			5
Southbank	✓	✓		✓		✓												4
Royal Botanic Garden		✓																1
Eureka												✓						1

Tower																	
Footbridge							✓							✓			2
Queens Bridge							✓							✓			2
Kings Bridge														✓			1
Spencer St														✓			1
Seafarers Bridge							✓										1
Webb Bridge							✓										1
Location Count	3	4	1	5	2	5	5	1	1	6	2	2	2	5	2	1	2	

Table 5: Mean Absolute Errors for different Travel Groups by fitting model

Model	**Group**			
	Australia	**Asia**	**Europe**	**North America**
Linear	3.527	2.901	2.917	<u>2.800</u>
Exponential	3.510	2.915	<u>2.916</u>	2.817
Quadratic	<u>3.388</u>	<u>2.654</u>	3.843	2.840